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Paying for Knowledge: Why People Paying for Live Broadcasts in Online Knowledge Sharing Community?

Shun Cai
Xiamen University, caishun@xmu.edu.cn

Qinfang Luo
Xiamen University, 372311485@qq.com

Xin Fu
Xiamen University, xfu@xmu.edu.cn

Guowei Ding
Xiamen University, Wiki_Ding@outlook.com

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Completed Research Paper

Shun Cai
Xiamen University, China
caishun@xmu.edu.cn

Xin Fu
Xiamen University, China
xfu@xmu.edu.cn

Qinfang Luo
Xiamen University
qinfangluo.xmu@gmail.com

Guowei Ding
Xiamen University, China
Wiki_Ding@outlook.com

Abstract

Powered by the proliferation of social computing and user-generated content, new knowledge sharing platforms in China, including Q&A communities and live broadcasting, were launched and received widely attentions recently. This research is motivated by the tremendous growth of an online knowledge sharing platform, Zhihu Live (www.zhihu.com/lives). Built upon Zhihu community, the usability and functionality of Zhihu Live makes it easy for user to create their own broadcasting lives that can be shared in the community to a wide range of audiences, making this an attractive platform to content creators (speakers) and knowledge consumers (audiences). We therefore propose a two-phase model to investigate the daily sales of Zhihu lives. Hierarchical Linear model was employed to test our hypotheses. Our preliminary results suggest that number of "like" positively affects daily sales before a live starts (phase 1), whereas "like" number, audience review score, and interactions between speakers and audiences during the broadcasting process have significant effects on live's daily sales after the live starts (phase 2). Implications are discussed and limitations are noted.

Keywords: knowledge sharing; Zhihu Live; signaling theory; knowledge products

Introduction

Knowledge sharing services in virtual communities enjoys tremendous growth in recent years. Powered by the proliferation of social computing and user-generated content, new services including Q&A communities, live broadcasting, were launched and received much attentions from participants. This research is motivated by the tremendous growth of a online knowledge sharing platform/community, Zhihu Live (www.zhihu.com/lives). Built upon Zhihu community, the usability and functionality of Zhihu Live makes it easy for user to create their own broadcasting lives that can be shared in the community to a wide audience, making this an attractive platform to content creators (speakers) and knowledge consumers (audiences). According to the report from Chinese Internet Consulting Data Center, the volume of users who are willing to pay for knowledge-based products soared 3 times in 2016, and the estimated economy scale of paid knowledge sharing service is about 10-15 billion RMB and this number reaches 30-50 billion RMB in 2017[1].

Zhihu Live is a real-time Q&A product whose registered users has exceeded one hundred million in September 2017[2]. On Zhihu Live platform, each user can be a speaker to broadcast lives and (s)he also can be an audience to purchase lives from other speakers. Similar to pre-ordering, a live is on sale a few days before the live starts. When a live start, audiences can interact with speakers and comment on lives. By charging audience who listen to live broadcast, Zhihu can presumably increase the platform's revenue and encourage more people to make a live broadcast because the platform would share their revenue with those speakers. Meanwhile, charging mechanism filter better-quality products from plenty of knowledge-based products. This dual nature of user participation, in content creation as well as knowledge consumption, as well as rich features of social interaction, is in contrast to earlier online communities. On Zhihu live platform, audience can propose questions or suggestion to the speaker of the live which they have bought, and then the speaker can respond audiences accordingly. This interaction results in the difference between paid knowledge sharing products and virtual or digital goods.

Although a number of researchers have investigated the factors affecting users' knowledge sharing behavior over the past decade (Chang and Chuang 2011; Chen and Hung 2010; Chia-Shen et al. 2012; Hsu et al. 2007; Koh and Kim 2004; Lin et al. 2009), research on online broadcasting lives has been scant. In particular, the pre-ordering mechanisms as well as the social interaction functionalities of Zhihu Live platform make it a special case in contrast to past knowledge sharing model. Therefore, we propose a two-phase model to investigate the sales of Zhihu lives. In the first phase, potential audience can pay for certain lives before the lives start. During this phase, audience relies heavily on the information about the speakers and brief introduction of a live to make purchasing decisions. In the second phase when the live begins, more information, including live reviews and interactions with speakers, are available for potential audience to make decisions. It is thus important to incorporate these into our second-phase research model.

Literature Review and Theoretical Background

Factors Affecting Purchasing Behavior in Knowledge Sharing

Researchers in knowledge sharing filed focused on defining factors that affect an individual's willingness to share knowledge: costs and benefits, incentive systems, extrinsic and intrinsic motivation, social capital, social and personal cognition and organization climate (Bock and Kim 2002; Bock et al. 2005; Chang and Chuang 2011; Chen and Hung 2010; Chia-Shen et al. 2012; Fang and Chiu 2010; Hsu et al. 2007; Koh and Kim 2004; Lin et al. 2009). However, as paid knowledge sharing business model becoming more and more popular, the study of examining factors that influencing purchasing behavior of paid knowledge product remains nearly blank.

The prior researches of information product are worth reference. For example, perceived benefit of online music products has a positive impact on purchasing behavior of a consumer(Chu and Lu 2007). Besides, consumers' willingness to pay for online content is positively related to their perception of convenience, essentiality, added-value, and service quality (Wang et al. 2005). For personal characteristic, a consumer's willingness to pay for digital content is related to age and gender (Punj 2015).

Signaling Theory

When focusing purchasing behavior, like any other business models, one of the most critical problems in paid knowledge sharing is information asymmetry. When decision makers are faced with information asymmetry, Spence (1973) postulated signaling theory, which explains that observable entity attributes can serve as a signal of quality. In his formulation of signaling theory, Spence (1973) utilized the labor market to model the signaling function of education. Potential employers lack information about the quality of job candidates. The candidates, therefore, obtain education to signal their quality and reduce information asymmetry.

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[1] Report from 199IT Chinese Internet Consulting Data Center: http://www.199it.com/archives/590711.html
[2] http://tech.qq.com/a/20170920/020694.htm

The signaling theory has been applied to a wide range of management studies, including electronic commerce research (Mavlanovaa and Koufaris 2012; Xu et al. 2013), online trust building(Yunjie et al.), venture capital financing, electronic word-of- mouth (eWOM)(Aggarwal et al. 2012), investor decisions (Davila et al. 2003; Higgins and Gulati 2006), and P2P lending(Cai et al. 2016). A review and assessment of the extant literature on the application of the signaling theory suggest that there are three primary focuses: signaler, signal, and the receiver (Connelly et al. 2015). In our study, the signaler in paid knowledge sharing could be the speaker, live, or other audiences, and the receiver might be the potential audience. The credibility of the source of information (i.e., the signaler) would affect the trustworthiness of the signals it sends out. From the receiver side, some receivers interpret signals differently from others. In many cases, receivers may apply weights to different signals in accordance with preconceived notions of their importance or cognitively distort signals (Perkins and Hendry 2010). Prior research has identified a variety of signals of quality. Not all signals are equally efficacious. Some signals may be strong or weak (Gulati and Higgins 2003). Two important traits for efficacious signals are observability and cost (Aggarwal et al. 2012; Connelly et al. 2015; Spence 1973). While observability is a necessary characteristic of a signal, it is not sufficient for detecting quality. Signal cost is so central to the signaling theory that some refer to it as the "theory of costly signaling"(Bird and Smith 2005). Some signals are costly to produce but more efficacious. For instance, the introduction of live chat software on online shopping sites might signal the quality to the consumer but might be expensive and time-consuming to employ.

Research Model and Hypotheses

The objective of this study is to examine the factors influencing sales of broadcasting lives. To capture various factors in different units, we proposed the following two-phase model for the scenarios of purchasing before a live starts (Model 1) and purchasing after a live starts (Model 2). For each model, we propose a two-level hierarchical model to investigate the daily sales volume of a live. The level-1 model represents the relationships among the daily-level variables and the level-2 model captures the influence of live-level factors. Formally, there are $i = 1, \ldots, n_j$level-1 units (e.g., daily sales record of $j$live) nested within $j = 1, \ldots, J$level-2 units (e.g., lives). Figure 1 shows the timeline of a live on sale.

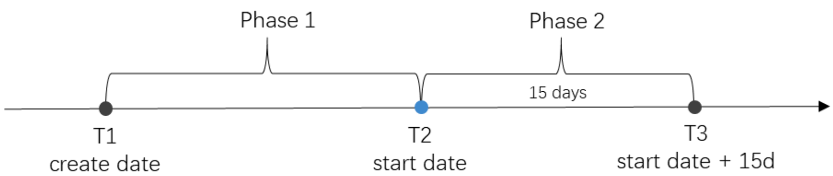

Figure1: timeline of a live

We distinguished two models for two major reasons. From information disclosure perspective, the information that a potential audience can receive in two phases are different. A speaker first creates a live, before it starts, potential audience can only get very limited information such as live price, some speaker information. However, an audience can make purchase in this phase. When a live start, potential audience can receive additional information about live such as review scores, comments, interactions between speakers and audiences, etc. Thus, purchasing behaviors in two phases are affected by different factors.

Figure2: snapshot of a live page before it starts **Figure3**: snapshot of a live page after it start

Figure 2 and Figure 3 are two snapshots of lives' pages before and after the live star respectively. For Model 1 (before a live starts), we identified four factors as the antecedents of daily sales volume, including the past cumulative sales volume, the number of people who liked a live, the degree of speaker being recognized in Zhihu and the price of a live. For Model 2, review score and interaction with the speaker are added as key antecedents of live sales. Two research models are presented in Figure 1 and Figure 2. Three variables are added as control variables, including speaker's gender, the degree of speaker's engagement in the community and tag popularity (measuring the popularity of a topic categories) in Zhihu Live. A description of variables is presented in Table 1.

Table 1: Description of Key Variables

Variable	**Description**
$SalesAftr_t$	Sales of a live in term t (phase 1, dependent variable)
$SalesBfr_t$	Sales of a live in term t (phase 2, dependent variable)
$Sales_{t-1}$	cumulative sales of a live in term t-1
$LvLkd_{t-1}$	cumulative number of users who like a live in term t-1
$LvRvwScr_{t-1}$	average review scores of a live in term t-1
$SpkrRcgn_{t-1}$	an index reflecting the degree of a speaker being recognized by others in Zhihu community, calculated as the average value of four factors: the number of gratitude from other users, the number of likes from other users, the number of times speaker's answers are mark "favorite" and the number of times speakers' answers are shared.
$Price$	the price of a live
Tag	the tag popularity of a live (control variable)
$Interaction$	the number of reply messages from the speaker to audiences of a live
$Gender$	speaker's gender of a live (control variable)
$contribution$	an index reflecting the contribution of a speaker in Zhihu community, calculated as the average value of: the number of ideas a speaker releases, the number of lives hosted by the speaker, the number of columns contributed by the speaker, the number of articles written by the speaker and the number of answers posted by the speaker. (control variable)

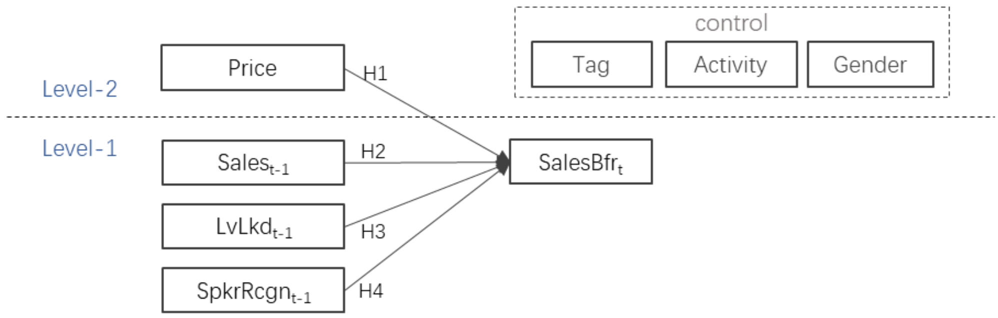

Figure2: Model 1 Pre-ordering Sales (a live is created but not yet start)

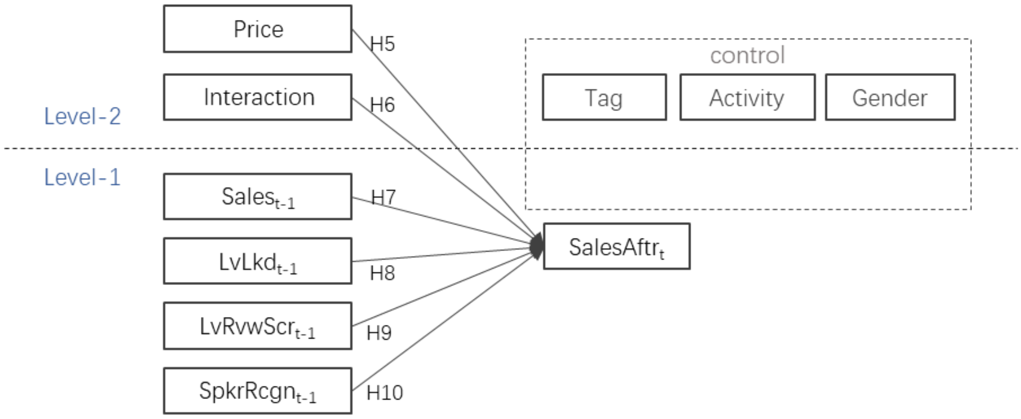

Figure 3: Model 2 Normal Sales (a live starts)

Dependent variable are the sales of a live in day *t* (we defined one day as a term). As commodity, price is obviously an important factor affecting buyer's purchasing behavior. In traditional economic theory, price has a negative impact on consumers' budgets (Rao and Monroe 1988). The higher the price is the grater the perceived monetary cost is, which impedes purchasing behaviors of consumers. Therefore:

H1: live price negatively affects the sales volume before a live starts. (first phase)

When making a decision, consumers evaluate not only cost but also benefit. The cost-benefit model of microeconomics holds that when a person is confronted with a set of possible actions each of which can lead to some set of outcomes, the person should convert the benefits and costs of all possible outcomes to a single scale, and adjust them for the probabilities that the outcomes will occur (Meade and Mishan 1972). In the purchasing scenario in our study, the benefit for an audience to purchase a live is the knowledge in this live. Thus, the extent of the benefit relies a lot on the quality of lives. However, during the first phase, the information about a live itself is limited. On the home page of a live, the number of people who have already bought a live is present. Based on signaling theory, past sales are usually considered as a quality signal and may arouse herding effect on potential audiences' decision making. A stream of research has documented evidence of herding effect. For example, music consumers seek frequently downloaded songs (Salganik et al. 2006); web visitors will be attracted to popular vendors according to click count that displayed on webpages (Tucker and Zhang 2011); customers prefer popular dishes when they consume in a restaurant (Cai et al. 2009). Therefore, we conjecture that:

H2: the past sales volume is positively associated with the current-period sales volume of a live before it starts. (first phase)

On Zhihu Live platform, each live can be marked with "like" and potential audiences can view the number of people who have liked when they browse the home page of this live. Besides, potential audiences can view all lives that they have liked in personal "liked list". Thus, when a potential audience is interested in a specific topic and he or she may "like" several lives in this specific topic, in order to make a further purchasing choice with the help of “liked list”. In this way the function of “like list” is quite similar with shopping carts of online shopping. Therefore, the “like” would play a role of quality signals and accordingly we conjecture that:

H3: the number of “like” is positively associated with the current-period sales volume of a live before it starts.(first phase)

Positive reputation over time is a strong signal of underlying quality (Coff 2002). In Zhihu Live community, the reputation of a speaker mainly shows in the approval of a speaker’s answers to other users’ questions, including the number of gratitude, the number of likes, the number of times that answers are collected and the number of times that answers are shared. We expect the degree of a speaker being recognized has a positive effect on sales. Therefore we conjecture that:

H4: The degree of a speaker being recognized in the community is positively associated with the current-period sales volume of a live before it starts. (first phase)

Model 2 corresponds to the scenario when audiences purchase lives after a live starts. During this phase, the information that viewed as signals can be divided into three categories according to diverse signalers: live, speaker and other audiences. The first kind factors are the information related to live directly including live price. Similarly, price is considered as monetary cost of consumers and has a negative impact on sales even after a live starting.

H5: live price is negatively associated with the current-period sales volume of a live after it starts. (second phase)

Besides price, the most import signal from live signalers is the interaction of a speaker with audiences. During a live, audiences who have made purchase can ask questions, post comments and expect the speaker to answer. The amount of messages that the speaker reply to audiences’ questions are showed in the homepage of a live. The more the amount of reply messages is, the larger the probability that a audience can get more useful knowledge from a live is. And the interactions also show the attitude of the speaker in sharing knowledge. Therefore, we conjecture that:

H6: the interactions between speaker and audiences of a live is positively associated with the current-period sales volume of a live after it starts. (second phase)

The second kind of factors is concerned with the signals from other audiences. The cumulated sales volume in the second phase also can be regarded as a strong quality signal and arouse herding effect on potential audiences’ decision making. Therefore,

H7: the past sales volume is positively associated with the current-period sales volume of a live after it starts. (second phase)

After a live starts, the amount of “like” involves more information than that before it starts. On one hand, it reflects the number of people who have willing to purchase a live, which is the same as the first phase. On the other hand, it indicates the quality of this live to some extent because a audience may mark a live if (s)he has already listened this live and indeed like it. Therefore, we suggest the following:

H8: the number of “like” is positively associated with the current-period sales volume of a live after it starts. (second phase)

Audiences who purchased a live have accesses to give a score and comment on the live after it starts. The review score is from one to five. The influence of user reviews is particularly important for experience goods (Klein 1998), because their quality is often unknown before consumption (Nelson 1970). In the past decades, studies have shown online reviews significantly affect the sales of products like movies, books and hotel rooms (Chevalier and Mayzlin 2006; Qiang et al. 2009; Reinstein and Snyder 2005). Moreover, a higher review score usually shows higher quality of a live, which means review scores can be regarded as a quality signal. Therefore,

H9: the review score of a live is positively associated with the current-period sales volume of a live after it starts. (second phase)

The last kind of factors is concerned with the signals from speakers. The degree of being approved of a speaker also has a positive impact on sales as it shows the ability of a speaker. The greater the speaker's ability is, the greater the probability that the live is superior is. Therefore, we propose:

H10: The approval degree of the speaker in the past is positively associated with the current-period sales volume of a live after it starts. (second phase)

Context and Data

The data used in this study were retrieved from Zhihu Live (URL: www.zhihu.com/lives), which is one of the largest paid knowledge sharing platforms in China. We obtained data by crawling the Zhihu Live website from December 17th 2017 to February 22nd 2018.Through the website, 222 lives were returned as search results. Three kinds of "noisy" records are removed in our study: 1) the records with missing value; 2) the lives whose create date is before Dec. 17th 2017 meanwhile the duration between start date and Feb. 22nd 2018 is less than 15 days; 3) the lives which have been in promotion. Particularly, the promotion programs of Zhihu lives are various (e.g., discount and combining selling) and the impact of promotion programs on sales are complex. We removed these records (only 4 lives) to control the effect of promotion and would do further research in our future study. After removing such "noisy" records, we retained 134 lives, including 1142 purchase records for Model 1 and 1884 purchase records for Model 2. There are 17 topic tags such as art, education, etc. in Zhihu Live platform and each live has only one topic tag.All data for independent variables were normalized before conducting the regression analysis.

In this study, variables in research models refer to two different hierarchies: daily sales and lives, which presents a nested data structure. For example,repeated observations are collected on a set of individual daily sales records and the measurement occasions are not identical for all sales records,each daily sales record is nested within some higher-level unit: a live.

Empirical Model and Results

Hierarchical linear model (HLM) is chosen for the data analysis to verify our research models.Within the hierarchical linear model, each of the levels in the data structure (e.g., repeated observations within sales records, sales records within lives) is formally represented by its own sub-model. Each sub-model represents the structural relations occurring at that level and the residual variability at that level. In our research, the level-1 models represent the relationships among sales record level variables and level-2 models captures the influence of live-level factors.

Model 1: Purchasing Before a Live Start

We include three control variables and four independent variables in the research model, particularly, one independent variable is at level-1 and the other three are at level-2. The following models for sales record i within live j was developed to examine Model 1:

(1) Model1a: Zero Model

Level-1:

$$SalesBfr_{ti} = \beta_{0i} + r_{ti}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + u_{1i}$$
$$\beta_{2i} = \gamma_{20} + u_{2i}$$
$$\beta_{3i} = \gamma_{30} + u_{3i}$$

In order to examine the whether the multiple hierarchies model is meaningful for our data, we first conduct zero model with random effect for sales. The results of zero model is showed in Table 2. Overall reliability equals 0.898. Intraclass Correlation Coefficient (ICC) is 60.32% (0.572 /

(0.572+0.376) = 60.32%), which means the difference of sales consist of 60.32% intraclass difference and 39.68% interclass difference. Thus, it is necessary to apply HLM.

(2) Model 1b: Random Coefficient Model

Level-1:

$$SalesBfr_{ti} = \beta_{0i} + \beta_{1i}Sales_{(t-1)i} + \beta_{2i}LvLkd_{(t-1)i} + \beta_{3i}SpkrRcng_{(t-1)i} + r_{ti}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + u_{1i}$$
$$\beta_{2i} = \gamma_{20} + u_{2i}$$
$$\beta_{3i} = \gamma_{30} + u_{3i}$$

To examine the impact of factors at level-1 on sales, we then apply random coefficient model with three independent variables: the past sales, the number of like, the degree of speaker being approved. The results suggested when a live is on pre-sale, the past sales volume of a live (β = 0.115, p = 0.000) has a positive impact on the amount of sales in current term, which support H2 in our study. Likewise, the cumulative amount of "like" of a live (β = 0.075, p = 0.010) positively affects sales in current term, which support H3 in our study. However, the effect of speaker's degree being recognized not significant, which fails to support H4. What's more, the variance component of level-1 in Model 1b is 0.289, which is lower than that in Model 1a (0.376).

For the relationship between the degree of speaker being approved and sales, there are several possible reasons. Firstly, on one hand, this index is computed from quantitative numbers from the platform and these numbers can be manipulated artificially. More specifically, a speaker on Zhihu community can increase his fans volume artificially. On the other hand, audiences now are sensitive to the Internet Water Army. Secondly, these numbers appear on the second page of a live but not homepage. Therefore, the extent of disclosure of this information may be lower.

(3) Model 1c: Full Model

Level-1:

$$SalesBfr_{ti} = \beta_{0i} + \beta_{1i}Sales_{(t-1)i} + \beta_{2i}LvLkd_{(t-1)i} + \beta_{3i}SpkrRcgn_{(t-1)i} + r_{ti}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}Price_i + \gamma_{02}Tag_i + \gamma_{03}Contribution_i + \gamma_{04}Gender_i + u_{0i}$$
$$\beta_{1i} = \gamma_{10} + u_{1i}$$
$$\beta_{2i} = \gamma_{20} + u_{2i}$$
$$\beta_{3i} = \gamma_{30} + u_{3i}$$

Factors like price at level-2 are added in full models to examine the impact of factors at level-2 on sales. Table 2 present the results of the regression. Unexpectedly, the effect of price on sales is not significant, which is not consistent with our hypotheses H1. There are two possible reasons for this consequence. Firstly, different buyers regard price as different signals. Some may consider it as cost signal and others may consider it as quality signal. These two effects are mixed. Secondly, some other difference among various lives are is missing in these models thus the price can not be a simple signal. A further research may be necessary.

Table 2: HLM Results for Model 1

Fixed Effect	**Model 1a**	**Model 1b**	**Model 1c**
(with robust standard errors)	**Coefficient with P-value**		
intercept	1.39*** (0.000)	1.39*** (0.000)	1.61* (0.011)
level 1			

$SalesBfr_{(t-1)}$		0.12*** (0.000)	0.98*** (0.000)
$LvLkd_{(t-1)}$		0.08** (0.001)	0.09** (0.015)
$SpkrRcng_{(t-1)}$		0.34 (0.710)	0.60 (0.207)
level 2			
$Price$			-0.46 (0.137)
Tag (control variable)			-0.14 (0.220)
$Contribution$ (control variable)			-0.03 (0.511)
$Gender$ (control variable)			0.07 (0.633)
Random Effect	**Variance Component**		
intercept	0.57	0.58	0.54
level-1	0.38	0.29	0.289
Random level-1 coefficient	**Reliability**		
intercept	0.90	0.91	0.94

Model 2: Purchasing When a Live is Over

The following models for sales record i within live j was developed to examine Model 2:

(1) Model2a: Zero Model

Level-1:

$$SalesAftr_{ti} = \beta_{0i} + r_{ti}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

$$\beta_{2i} = \gamma_{20} + u_{2i}$$

$$\beta_{3i} = \gamma_{30} + u_{3i}$$

The results of zero model is showed in Table 3. Overall reliability equals 0.912. Intraclass Correlation Coefficient (ICC) is 65.51% (0.429 / (0.429 + 0.226) = 65.51%). Thus, difference of sales consists of 65.51% intraclass difference and 34.49% interclass difference. HLM is properly to examine the research question.

(2) Model 1b: Random Coefficient Model

Level-1:

$$SalesAftr_{ti} = \beta_{0i} + \beta_{1i}Sales_{(t-1)i} + \beta_{2i}LvLkd_{(t-1)i} + \beta_{3i}LvRvw_{(t-1)i} + \beta_{4i}SpkrRcng_{(t-1)i} + r_{ti}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

$$\beta_{2i} = \gamma_{20} + u_{2i}$$

$$\beta_{3i} = \gamma_{30} + u_{3i}$$

$$\beta_{4i} = \gamma_{40} + u_{4i}$$

Random coefficient model is applied to test the impact of factors at level-1 on sales. The results indicate that on the second phase, the past sales volume of a live (β = 0.123, p = 0.000) and the cumulative amount of "like" of a live (β = 0.093, p = 0.000) both positively affects sales in current term, which support H7 and H8 in our study. Besides, reviews scores of a live (β = 0.466, p = 0.000) also has a positive effect on sales and this result is consistent with H9. While the effect of speaker's degree being recognized is not significant again as the result in Model 1, which fails to support H10. In addition, the variance component of level-1 are both is 0.158in Model 2b and0.226 in Model 2a, which is reduced by 30.13%.

(3) Model 1c: Full Model

Level-1:

$$SalesAftr_{ti} = \beta_{0i} + \beta_{1i}Sales_{(t-1)i} + \beta_{2i}LvLkd_{(t-1)i} + \beta_{3i}LvRvw_{(t-1)i} + \beta_{4i}SpkrRcng_{(t-1)i} + r_{ti}$$

Level-2:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}Price_i + \gamma_{02}Interaction_i + \gamma_{03}Tag_i + \gamma_{04}Contribution_i + \gamma_{05}Gender_i + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

$$\beta_{2i} = \gamma_{10} + u_{2i}$$

$$\beta_{3i} = \gamma_{10} + u_{3i}$$

$$\beta_{4i} = \gamma_{10} + u_{4i}$$

To examine the impact of factors at level-2 on sales factors, at level-2 are added in full models and table 3 present the results of the regression. The effect of price on sales is not significant from the perspective at level-2, which fails to support H5. However, the degree of interaction (β = 0.155, p = 0.000), thus supports H6 in our research. This consequence reveals that most buyers believe interaction between speaker and audiences is a quality signal when making purchasing decision.

In the second phase, the reason for the relationship between price and sales may be different from the first phase. When a live is over, there are some new information can be regarded as quality signals such as review scores. Thus, users usually consider price as a cost signal in this phase. But each knowledge-based product is unique, so the heterogeneity makes the comparability of cost ineffective.

Table 3: HLM Results for Model 2

Fixed Effect	**Model 2a**	**Model 2b**	**Model 2c**
(with robust standard errors)	**Coefficient with P-value**		
intercept	1.140*** (0.000)	1.134*** (0.000)	1.612* (0.012)
level 1			
$SalesAftr_{(t-1)}$		0.123*** (0.000)	0.162** (0.001)
$LvLkd_{(t-1)}$		0.093*** (0.000)	0.091** (0.001)
$LvLvRvw_{(t-1)}$		0.466*** (0.000)	0.596** (0.001)
$SpkrRcng_{(t-1)}$		-0.177 (0.663)	-0.196 (0.823)
level 2			
$Price$			-0.165 (0.199)
$Interaction$			0.155*** (0.000)
Tag (control variable)			-0.082 (0.344)
$Contribution$ (control variable)			-0.048 (0.214)
$Gender$ (control variable)			0.016 (0.913)

Random Effect	Variance Component		
intercept	0.429	0.427	0.387
level-1	0.226	0.158	0.156
Random level-1 coefficient	**Reliability**		
intercept	0.912	0.980	0.978

Conclusions

This study contributes the knowledge sharing research by revealing the factors that affecting the sales of knowledge products in sharing economy. We addressed this issue by examining which factors are powerful signals that lead potential buyers more likely to make a purchasing decision. More importantly, from a cross-hierarchy perspective, we examined the influence of different factors on sales volume of live with time series data, so that control the endogeneity among variables. Our study shows that 1) herding effect exists in purchasing behavior of knowledge sharing products. Both the amount of people who like a live and the amount of people who have bought a live have a positive impact on the current amount of sales; 2) interaction may add more value to the knowledge product and consequently increase sales; 3) price has no impact on sales of knowledge sharing products may due to two possible reason: small data size and the unique feature of knowledge sharing product. The unique of each product comes from the difference of sharers and interactivities between sharers and receivers during the sharing process. However, in previous research, we examine the effect of price on the total sales for a live and the empirical results shows the negative relationship between them.

However, there are still some limitations to the current research. Firstly, we collected only data from one knowledge sharing platform (Zhihu Live) that may have unique characteristics, limiting the generalizability of the proposed model. Secondly, the time span of data is too short so that the secular trend of sales can not be observed. Last but not least, text information such as identity authentication is missing in this study, which may suggest that there are other important factors for this model that have not been considered.

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